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TOWARD A METHODOLOGY FOR MAN-MACHINE FUNCTION ALLOCATION IN THE AUTOMATION OF SURVEILLANCE SYSTEMS. VOLUME I. SUMMARY

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VOLUME I: SUMMARY

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A study was conducted to determine some of the performance implications of various degrees of automation in surveillance systems. The objective was to aid system designers of future surveillance systems in making trade-off decisions. A general functional taxonomy of surveillance systems was developed and each function was considered in terms of the necessity of operator involvement versus the likely success of full automation, based on the present state-of-the-art and knowledge of recent successes and failures in automating surveillance system functions.

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A model of human information processing in surveillance systems was also developed and various strengths and weaknesses of surveillance system operators were discussed in relation to the elements of the model. Observations were made on the extensive individual differences in performance among surveillance system operators and some of the reasons for these differences. Consideration was given to special problems in the design of system tests and evaluations, given these extensive operator performance differences, and several other variables typically associated with surveillance system operations. The performance of superior operators as a design model for automation in surveillance systems was discussed.

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Volume I: Summary

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VOLUME I: SUMMARY

CHAPTER 1

INTRODUCTION AND OVERVIEW

This is Volume I of a two-volume report on a study concerned with the performance implications of various degrees of automation in surveillance systems. The study was stimulated by a growing need for systematic feedback from operating systems to the designers of future systems. The need for such feedback was felt to be especially acute in the class of systems generally known as information processing systems, of which surveillance systems are an example. It was hoped that the study would generate information that could aid system designers in making performance/cost trade-off decisions in future surveillance systems.

It was felt that the most significant feature of current and future information processing systems is the extent to which they incorporate computers and other forms of automation. A trend toward more and more dependence on automation has been especially evident in recently developed surveillance systems. Both the cost and performance implications have proved to be extensive, and there have been some major disappointments in how effectively some functions can be automated.

In some kinds of systems, the performance improvement due to automation has been quite dramatic. For example, automatic processing, storing, and distribution of information in tactical data or command-and-control systems can immensely facilitate the making of timely and valid decisions. Automation is especially effective in such systems because, in general, human beings are severely limited in the information rate they can handle and, consequently, often become

overloaded. Also, the nature of most of the information in tactical data systems is such that it is not degraded by automatic processing and distribution. In contrast, automation techniques can often lead to severe performance degradation when they are applied to complex recognition and decision-making functions.

Most system functions lie somewhere between these extremes. Often, the information processing load is sufficiently high that automation is tempting. However, it may be clear that *some* performance degradation will be incurred. Just how much degradation to expect is seldom easy to predict.

It was our purpose to address this problem in surveillance systems using four sources of information: (1) experience with automation in several large-scale surveillance systems during the course of their development and trial, (2) an analysis of what is known about how man functions as an information processor, (3) test data on how well man performs various tasks associated with the operation of surveillance systems, and (4) data from experiments specifically designed to clarify the effects of function allocation between man and computer in surveillance systems.

A good deal of this study was retrospective in the sense that we had to depend on past histories of successes and failures of automation in surveillance systems at various stages of development. And we are certainly not in a position to forecast how the future state-of-the-art in automation will cope with some of the difficulties identified during the course of this study; but we *can* assert the importance of closing the feedback loop from operating systems to the designers of future systems. We hope that the material in these two volumes will help serve this purpose with respect to both machines and their human operators. There is still a good deal of uncertainty about both. The following quotation, which was made a decade ago, still retains the clear ring of truth:

> Those of us who are in the human sciences often feel insecure and apologetic about our own science and subject matter. We often feel that it is our ignorance about human behavior which is responsible for the difficulties we have in making decisions about man-machine system design. If you have ever worked closely with systems engineers, however, you soon come to realize that there is much uncertainty on the machine side of the equation as well. In the first place, there is no such thing as *a* system design process, precise and specifiable.... Instead, systems designers often proceed with much trial-and-error just as anyone else does. In addition, although I realize it is dangerous to make a generalization about this point, I have the feeling that engineers are sometimes overly optimistic in their predictions about what they can do with their machines. As a result, the final products frequently fall short of what had been anticipated for them. (Chapanis, 1965)

There is still much ignorance about human behavior, there is still much uncertainty on the machine side of the equation, there is still no such thing as *a* system design process, and engineers are still sometimes overly optimistic about what they can do with their machines. Despite substantial engineering efforts to automate most surveillance system tasks, extensive automation is conspicuously absent from today's operational surveillance scene. A large proportion of these efforts have been focused, by several different engineering groups, in several different ways, upon certain crucial surveillance system functions which continue, obstinately, to resist successful automation. It now appears to many that successful automation of these functions is *not* just around the corner, and the time appears propitious for a serious reconsideration of man-machine function allocation in the automation of surveillance systems.

We say "propitious," implying a favorable condition, not because things have been going well; quite to the contrary. It is the sheer magnitude and costliness of the problems which have been encountered that, perhaps, will provide the necessary impetus for the substantial interdisciplinary efforts that will

be essential to resolve the function allocation problems we are now clearly confronted with. Many years ago, human factors specialists could specify with a reasonable degree of precision how well each of several surveillance system functions and tasks could be executed by men, but it was not then possible for engineers to demonstrate corresponding performance levels for machines. In the absence of empirical evidence, a good deal of optimism prevailed regarding automation. Today, the strengths and weaknesses of machines, as well as men, are more clear; and while it is obvious that we will not want to cling to "totally" manual systems, the extensive degree of automation anticipated by some cannot be regarded as a viable alternative for "next generation" systems, either. Thus, human factors specialists and systems engineers must now undertake, together, to move into those uncertain regions where man and machine work as more nearly equal partners, executing tasks apportioned in various permutations, so that it may be determined which configurations bring about the synergistic man-machine relationships that must comprise the "next generation" systems.

We do not believe the human factors and systems engineering disciplines are totally prepared for the function allocation problems that now must be faced. We have entitled this report *"Toward a Methodology..."* because it is not a "cookbook," with convenient recipes for every (or any) *specific* function or task allocation. Indeed, the complete "cookbook" of function allocation recipes would probably take longer to develop than the totally automated surveillance system, therefore rendering it moot; but neither of these remote developments should concern the surveillance community faced with solving problems now.

We have set down in the two volumes of this report a perspective of the function allocation process as we see it affecting the "next generation" of systems. Some of this information, we hope, will make the task of the reader seriously

involved with specific function allocation problems easier, and we will have achieved an important goal if this report will provide him some guidance regarding the precise nature of the information gathering that he will almost certainly have to undertake himself.

Classified information, which comprises much of the specific information in Volume II, has been omitted from Volume I to permit a broader dissemination of summary information, with the result that some of the viewpoints expressed in this volume may seem unsupported. We hope that the interested reader will also turn to Volume II, the contents of which are briefly outlined at the end of this volume.

The following chapter outlines a general functional taxonomy of surveillance systems, together with our conclusions concerning the merits and problems associated with allocating each function to man or computer. Volume II also contains the taxonomy, but with some examples that are classified, and a somewhat extended discussion of each function. Chapter 3 presents a model of man as an information processor in surveillance systems; Chapter 4 presents some information on the variable performance of man in surveillance systems; and Chapter 5 is concerned with the measurement of man-machine performance in surveillance systems. Each of these chapters has its more detailed counterpart in Volume II.

CHAPTER 2

MAN-MACHINE FUNCTION ALLOCATION IN NEW SYSTEM DESIGN

One of the products of this study is a generalized taxonomy of surveillance system functions. We shall discuss each of these functions, breaking them down into elements we shall call "tasks." The reader should note that we use the term "task" in a special sense that shall be presently evident, and that the term has been used by different authors to mean different things. Each of the taxonomy functions is described below. A rating is given to each task on a scale from 1 to 9, which reflects our conclusions concerning the necessity of retaining operator involvement in that task versus the alternative of full automation. A high Operator Involvement Rating (7, 8, or 9) is assigned to a task that almost certainly requires extensive roles for the operator at this time, either because extreme difficulties have been encountered in previous attempts to automate such tasks or because potential sources of difficulty can readily be foreseen. A low Operator Involvement Rating (1, 2, or 3) is associated with tasks that clearly should be automated because of man's limited information processing capabilities, computing capabilities, or fallible memory, and because it has been demonstrated that machines can handle those tasks efficiently. Intermediate OIRs are given to those tasks where human information processing currently plays a critical role but where computer-aiding may nonetheless be a feasible and desirable system characteristic.

We had some misgivings about assigning simple unidimensional scores to the admittedly very complex considerations of function allocation. We nevertheless did so because we feel these numbers do convey in a very generalized manner a convenient index to the very different degrees of risk in

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making the assignment of various functions to men or machines. We readily admit that there may be considerable room for argument about the different values assigned; this satisfies one of our objectives because we feel such arguments may be useful.

The reader will find a rationale for each rating in the function descriptions that follow Table 2.1. The discussion that follows is general and somewhat abstract. The interested reader is urged to consult Volume II, in which the discussion is more lengthy and is enhanced by examples drawn from specific (classified) surveillance systems.

TABLE 2.1

SURVEILLANCE SYSTEM FUNCTION TAXONOMY

		Operator Involvement Rating (OIR)
1.	Memory	
1.1	Goal information	5
1.2	Function algorithms	5
1.3	Stimulus data	2
1.4	Non-stimulus data	5
2.	Executive Control	
2.1	Comprehension of the current situation	5
2.2	Interpretation of goals	5
2.3	Interpretation of past situations	5
2.4	Hypothesis generation and prediction	5
2.5	Effecting appropriate control responses	5
2.6	Hypothesis testing and iteration	5
3.	Attention Selection	
3.1	Search initiation	6
3.2	Sensor placement	6
3.3	Spatial coverage and spatial resolution selection	5
3.4	Selection of other parameters	5

		Operator Involvement Rating (OIR)
4.	Stimulus Transmission	
4.1	Pre-sensor transmission	N/A
4.2	Post-sensor transmission	1
5.	Stimulus Processing	
5.1	Beam forming	1
5.2	Further processing	1
6.	Detection	
6.1	Signal detection	2
6.2	Transient detection	8
6.3	Track detection	3
7.	Feature Extraction/Association	
7.1	Signal parameter estimation (i.e., extraction of lowest-order features)	6
7.2	Screening	6
7.3	Early classification based on especially distinctive *characteristic* lower-order features	2
7.4	Association of lower-order features into appropriate higher-order features	8
7.5	Alerted searching for undetected lower-order features	2
7.6	Association of higher-order features with targets	8
7.7	Early classification based on especially distinctive *characteristic* higher-order features	2
8.	Feature Space Transformation	
8.1	Combination of features to reduce dimensionality	5
8.2	Combination of features to maximize discriminability	5
8.3	Coordinate transformation	1
9.	Target Localization	
9.1	Single-sensor fixing	2
9.2	Multiple-sensor fixing	2
9.3	Tracking	2

		Operator Involvement Rating (OIR)
10.	Target Motion Analysis	
10.1	Inference of motion based on extracted stimulus features	2
10.2	Position-versus time analysis	2
10.3	Track-aiding	2
11.	Classification	
11.1	Determination of stimulus source likelihood estimates	5
11.2	Alerted searching for undetected signals typically related to inferred stimulus sources	2
11.3	Determination of stimulus source configuration likelihood estimates	4
11.4	Determination of operating behavior likelihood estimates	7
11.5	Determination of target class likelihood estimates	3
11.6	Alerted searching for undetected signals typically related to inferred target classes	3
11.7	Determination of target class *a priori* probabilities	4
11.8	Determination of target class *a posteriori* probabilities	2
11.9	Determination of classification decision risk functions	3
11.10	Determination of an appropriate decision rule	2
11.11	Classification decision making	3
12.	Communication	
12.1	System coordination	3
12.2	System output	3
12.3	System input	3
13.	Learning	
13.1	Strategic and tactical intelligence	5
13.2	Technical intelligence	5
13.3	System operational characteristics	5
13.4	Training	5

1. *Memory*. Memory is essential for even the simplest system to operate. In simple systems, memory might be regarded as the hard wiring which causes the unit to behave as it does. In larger systems, memory can be widely distributed, in many different forms, throughout the system. It serves as a repository for "goal" information, to assist the executive function in bringing about goal-directed system behavior; for the storage of function algorithms, which can include all the functions on our list; for the storage of stimulus data, upon which the function algorithms work; and for the storage of non-stimulus data, which are many in kind and number and which are necessary to support the operation of the system. Crucial factors of the memory function include form, capacity, storage speed, storage accuracy, retrieval speed, and retrieval accuracy.

Man's own memory is often called upon to provide a substantial proportion of system memory. Goal information, function algorithms, and non-stimulus data are likely to be associated with man's long-term memory; stimulus data, with man's iconic and short-term memories (see Chapter 3). Man's memory has an astonishingly great *capacity*, but most of the stored information is totally irrelevant to functions he is likely to perform in surveillance systems; its *storage speed* and *accuracy* are highly dependent upon both the man and the learning situation; its information *retrieval speed* can be annoyingly slow; and its *retrieval accuracy* is certainly unreliable relative to hardware memory systems. Nevertheless, man's own memory, when acting in support of his more sophisticated behaviors, such as hypothesis formulation or pattern recognition, is an invaluable resource which is difficult or impossible to duplicate with engineered mechanisms.

Allocation with respect to the memory function is discussed in terms of four tasks: (1) goal information, (2) function algorithms, (3) stimulus data, and (4) non-stimulus data.

1.1 *Goal information*. . . . . OIR: 5

The memory function must provide storage of goal information so that the executive control function (see below) can attempt to bring about system goal-directed behavior. This goal information should reflect system strategic, tactical, and technical employment considerations, with specific information relating the importance and probability

of occurrence of various targets of interest to pertinent system capabilities and limitations.

1.2 *Function algorithms* . . . . OIR: 5

All system functions we describe must in some sense be embodied in system memory. We earlier noted that hard wiring constitutes a form of memory. Another example is when a function is executed entirely by a computer. In that case, the function algorithm can be precisely identified (consisting of a string of machine instructions) and its location in system memory can be precisely identified physically. Another, very important, example is when a function is allocated entirely to man; in that case neither the function algorithm nor its physical location can be precisely defined. Yet the importance of man's memory is indisputable, since his behavior, which is crucial to system functioning, depends upon it.

1.3 *Stimulus data* . . . . OIR: 2

In surveillance systems, it is often necessary to acquire, store, and display large amounts of stimulus data.[1]

A common storage medium for stimulus data has been "hard-copy" displays. This medium has well served surveillance systems, but it has limitations. One is the physical space required. One alternative is to store many millions of bits of information in such a manner that they may be retrieved for display in a timely manner. Another, generally unacceptable, alternative is not to store the stimulus data but to rely instead upon real-time system functioning not to overlook anything of importance. This is very risky. Reliance upon the real-time functioning to select only a portion of the stimulus data for storage sometimes leads to serious loss of information. Thus, in some surveillance systems, the stimulus data generate a substantial memory requirement that should be allocated to machines if hard-copy storage is not feasible.

[1]We use the term "stimulus" rather than signal or signal-plus-noise or signal-plus-noise-plus-clutter because the definitions of signal, noise, and clutter can change dynamically as the system is in operation, but these things all remain stimuli.

1.4 *Non-stimulus data* . . . . OIR: 5

Much non-stimulus data is necessary for a surveillance system to operate. Most data are technical intelligence about targets of interest (and, importantly, targets *not* of interest). In early systems, a common storage medium for such data was the printed page, in the form of technical publications. Even in the latest systems, the printed page remains important, not only for technical intelligence, but also for information regarding the knob and dial operation of hardware. Printed operating data gradually transfer (with varying degrees of fidelity and comprehensiveness) to the operator's own memory through learning. His memory constitutes a second storage medium for these data and, when a complex function such as classification is attempted by computer, these data will be found in a third medium of storage, the computer memory. There (and in man, since we intend to model him in decision-theoretic terms), these data are likely to be represented in some combination of *a priori* probabilities, likelihood functions, risk functions, and decision rules. Somewhere among the non-stimulus data should be recorded the sum total of the system's past "experience," so that the system (i.e., the executive control function) can deal with the present through historical perspective of the past.

2. *Executive Control.* In complex systems, we believe the executive control function necessary to bring about integrated, goal-directed system behavior. This function, like others, may be executed either by man or machine. Most commonly it has been within man's province. Some of the crucial factors relating to the attainment of appropriate goal-directed behavior include (1) the ability to define system goals, (2) the ability to implement procedures to attain system goals, and (3) the ability of the executive faithfully to execute the procedures.

Executive control requires interpretation of information in memory concerning goals and past situations, comprehension of the present situation, hypothesis generation, prediction, effecting appropriate control responses, hypothesis testing, and subsequently appropriate iteration. The above are highly cognitive activities which man performs with varying degrees of effectiveness. Man's variability is one of his weaknesses as an executive. On the other hand, such activities are very difficult to automate successfully.

Executive control must exert its influence throughout a very complex range of activities, from those requiring wide focus upon the most molar aspects of system functioning to those requiring narrow focus upon molecular detail. However, there are certain tasks characteristic of executive control at all of these levels, and we will discuss function allocation with respect to each of them in turn: (1) comprehension of the current situation, (2) interpretation of goals, (3) interpretation of past situations, (4) hypothesis generation and prediction, (5) effecting appropriate control responses, and (6) hypothesis testing and iteration.

2.1 *Comprehension of the current situation* . . . . OIR: 5

The executive function makes its control responses based upon its comprehension of the current situation, in an attempt to make that comprehension more accurate. The executive control function is adaptive. Through iteration, it attempts to converge upon a true perspective, which is the fundamental goal of any surveillance system. Accurate comprehension of details of the situation at the outset hastens convergence and reduces the probability that divergent behavior may evolve.

2.2 *Interpretation of goals* . . . . . OIR: 5

The executive control function interprets the goal information stored in memory in the light of its perspective upon the current situation in order to bring about proper allocation of system resources.

2.3 *Interpretation of past situations* OIR: 5

The executive control function should interpret the record of past situations for its relationships to the current situation. This activity represents an "experience factor" which may have considerable influence upon the control responses made in the current situation.

2.4 *Hypothesis generation and prediction.* . . . . OIR: 5

Based upon the executive's comprehension of the current situation and its interpretation of system goals and past situations, it will (ideally)

form hypotheses and make predictions. For example, the executive may determine that a target is of special interest and worthy of greater attention; more, that if the target is of a certain type, there should be present a particular signal feature not yet detected.

2.5 *Effecting appropriate control responses* . . . . OIR: 5

Based upon predictions from the preceding task, the executive should effect appropriate control responses. These may be preliminary, intermediate, or final output responses. To continue our example (see 2.4), if the executive predicts that a particular signal feature should be present, it should focus system attention to heighten search for that feature.

2.6 *Hypothesis testing and iteration.* OIR: 5

After effecting control responses, the executive tests its hypotheses and predictions upon the stimulus set. Let us continue our example: A predicted target signal is sought. If found, it strengthens its associated hypothesis; if not, the hypothesis is weakened or rejected. After such a test, executive comprehension of the current situation refines itself. Then executive control iterates its tasks, leading to continued refinement and, hopefully, convergence on a solution.

3. *Attention Selection.* The objective of this function is to receive all necessary stimuli to attain system goals. This means maintaining surveillance of a sufficient area of stimulus space with sufficient resolution. The area to be searched is multidimensional, including (1) the three dimensions of Euclidean space; (2) time; and (3) various signal-related dimensions, such as intensity, frequency, polarization, and so on. The crucial limitation in attention selection is that the quotient of the multidimensional stimulus area to be searched divided by the resolution with which that area is searched has an upper bound. Since information processing rate has cost and technical constraints, a trade-off is forced between the area of stimulus space surveyed and the resolution possible within that area. The problems involved in making this trade-off are substantial.

(Man has his own, very interesting, attention-selection mechanism, which is discussed at length in Chapter 3.)

The attention selection function is considered in terms of four tasks: (1) search initiation, (2) sensor placement, (3) spatial coverage and spatial resolution selection, and (4) selection of other parameters.

3.1 *Search initiation* . . . . OIR: 6

This task has its most obvious meaning in connection with certain systems that do not ordinarily conduct a continuous surveillance operation, such as certain airborne acoustic ocean surveillance systems; their search must be initiated by a communication from the proper authority. This communication must define with some degree of certainty the area which is to be searched, which constitutes the first step in attention selection. However, even in systems which conduct continuous surveillance operations, search initiation still has meaning, for it may refer to an intensification of search in some portion of the area under continuous surveillance; we shall refer to this as "alerted search." Alerted searching may be brought about through communication of information from outside the system, or it may be initiated by the system executive function as part of its hypothesis formulation, prediction, and testing iteration.

3.2 *Sensor placement*. . . . . OIR: 6

For systems whose sensors are fixed, this task hopefully has only to be considered once. However, for mobile systems, the sensor placement task constitutes the next step in attention selection following search initiation, and obviously defines to some extent the spatial coverage of the system.

3.3 *Spatial coverage and spatial resolution selection*. . . . . . . OIR: 5

In some systems, spatial coverage and spatial resolution are not variable, but are fixed at the time of installation (granted, operators may not give equal attention to all spatial areas the system senses). However, other systems do provide flexibility in these respects. Variable

coverage and resolution are particularly important when there is limited data processing capacity and it is necessary simultaneously to cover all potentially accessible spatial areas.

3.4 *Selection of other parameters* . . OIR: 5

Most large systems have a large number of mode options and control settings which must be properly selected to focus the system's attention and permit optimum performance. When these selections are made by an operator, it frequently poses a significant challenge to him to do so effectively; when the selections are automated, it often poses a significant challenge to the designer to provide adequate flexibility in his mode-selection algorithms to responsively maintain optimality in the face of changing environmental and operational conditions.

4. *Stimulus transmission.* The goals of this function are to convey stimuli to the system sensors and then to other system elements as necessary. A crucial factor affecting stimulus transmission is the environmental channel. Another is that channel bandwidths have cost and technical limits which force trade-offs among types of information transmitted, encoding/decoding methods, and transmission rates.

One of the most crucial links in man-machine interaction is at the interface where stimulus transmission occurs from machine to man. This is particularly true when the complex stimuli of a surveillance system are presented visually to an operator who must perform, or augment the machine in performing, detection, feature extraction, and classification. Display hardware/software technology is in a relatively advanced state compared to our knowledge of the optimal formatting of complex information for presentation to the operator. Much more experimental work is needed to add to this knowledge, particularly in the face of the trend toward displaying more information (including new kinds of information derived from more advanced stimulus processing) to fewer operators.

The stimulus transmission function is considered below in terms of two basic tasks: (1) pre-sensor transmission, and (2) post-sensor transmission.

4.1 *Pre-sensor transmission*. . . . . . OIR: N/A

The environmental medium which conveys stimuli to the sensor may have substantial effects on those stimuli, so the nature of the transmission medium

must be well understood. Many of the apparent vagaries of various transmitting media have given way to knowledge and understanding in the face of research. Still, there is much that remains to be known, and that which we may discover holds the potential for advanced *stimulus processing* techniques. There is little doubt that processing will remain the province of machines.

4.2 *Post-sensor transmission* . . . . . OIR: 1

Once the stimuli have been converted to electrical signals, they must be routed throughout the system. When the system is sufficiently compact physically that the signals may be carried by wires, there is not much of a problem. However, when parts of the surveillance system are so separated that electromagnetic transmission is necessary to convey data, the quantity of those data, the rate at which they are generated, and the need for security in their transmission conflict with cost and technical constraints upon channel bandwidth.

5. *Stimulus processing*. The goal of this function is to process stimuli to support the detection and feature extraction functions. This simple statement belies the complexity and importance of the function. The crucial factors here involve the determination of optimal processing; the implementation of optimal processing; and the provision of sufficient processing flexibility to maintain optimality with changing conditions. Different signals may require different processing, but processing rate is limited by cost and technical constraints, requiring multiplexing trade-offs.

In surveillance systems a large amount of stimulus processing is done electronically. Electronic processing enormously extends man's own sensor capabilities. Some of the most significant performance improvements in the evolution of surveillance systems have resulted from advancements in signal processing technology. However, at some point the processed stimuli are usually presented to an operator, at which point his own stimulus processing must come into play.

The stimulus processing function is considered in terms of two tasks: (1) beam forming, and (2) further processing.

5.1 *Beam forming*. . . . . OIR: 1

To provide resolution in physical space, surveillance system sensors are usually formed into arrays. The

outputs of array sensors are combined in various ways to provide directional sensitivity. Beam-forming, in addition to providing spatial resolution, also improves signal-to-noise ratio. In general, the narrower the beam the better the ratio. But narrow beams also mean that more beams are necessary for the same coverage, and therefore greater processing and display requirements for the system. Recent advances include adaptive beam forming, which enables the system to respond to changing signal and noise conditions. Most aspects of beam forming do not involve operator intervention.

5.2 *Further processing*. . . . . OIR: 1

A number of additional processing techniques may be employed to enhance specific characteristics of a complex stimulus. These are almost always best accomplished with machines.

6. *Detection*. The goal of this function is to detect the presence of stimuli of interest in the total stimulus set with sufficient speed and accuracy. This is a complex problem that requires knowledge of stimuli of interest, of the stimulus set exclusive of stimuli of interest, and awareness of man versus machine capabilities/limitations. In many existing systems, man performs all detection tasks. When target signal characteristics are well known, detection can usually be more effectively accomplished by machine.

Function allocation with respect to detection is considered in terms of three tasks: (1) signal detection, (2) transient detection, and (3) track detection.

6.1 *Signal detection* . . . . OIR: 2

Signal detection consists of vertical or azimuthal search for signal sources, by comparing the energy received on one bearing or elevation with that received on adjacent bearings or elevations. Signal detection is probably best modeled in a sequential decision-making context (Birdsall & Roberts, 1965). In this model, two decision thresholds are of interest. If the received energy (or some test statistic derived therefrom) exceeds the higher of these thresholds, it is decided that a signal is present. If the energy or test statistic falls between these two thresholds, it is decided to wait for additional information. And (in the classical model) if the energy or test statistic falls below the lower of these thresholds, it is decided that

no signal is present. In many cases, the lower of these two thresholds is inconsequential, since the system or operator makes no overt response which would differentiate between a decision to continue searching and a decision that no signal is present. However, in other circumstances it is indeed consequential: Consider the case of an alerted search for a signal which must either be confirmed or denied in order for the executive-control function to test predictions and refine hypotheses.

6.2 *Transient detection* . . . . OIR: 8

The dictionary tells us that a transient "is short in duration and passes quickly." The question is, compared to what? For surveillance systems there are several frames of reference within which the definition might differ; in all, however, transients are "things that happen somewhat more quickly than most of what is going on." Whatever the frame of reference, many transients share two common characteristics: 1) They may represent important information, and 2) they may be difficult to detect automatically. Provided sufficient signal-to-noise ratio, man's perceptual mechanisms make many transients easily detectable on a suitable display. Automating their recognition and characterization is far from easy, and far from successful implementation in any automatic system. (This accounts, we believe, for the rather conspicuous shortcomings of some highly automated systems we have seen).

6.3 *Track detection* . . . . OIR: 3

Target motion parameters are extremely important in surveillance systems, both for maintaining contact and to assist in determining the tactical and strategic implications of threat targets. Track detection, and target localization and motion analysis, can be most precisely executed using the outputs of several sensors at geographically separated locations.

7. *Feature extraction/association*. The goals of this function are to extract relevant features from the stimuli of interest, associate these features where appropriate, and extract relevant features resulting from the association in an iterative, hierarchical process of extraction and aggregation, leading to more and more features. The crucial factors are definition of relevant features and of appropriate associations, and the development of feature extraction and association methodologies. These

processes are complicated by the necessity for invariance to irrelevant transformations or changes in the stimulus set, and adaptability to relevant transformations or changes in the stimulus set.

For signals with stationary probability distributions, machines can exceed man in reliability, accuracy, and speed of signal parameter estimation. However, estimation of parameters which characterize non-stationary signals is probably best performed by man. Likewise, screening can often be efficiently performed by man, since his attention selection mechanisms permit him to ignore stimuli that are not of interest and attend to those that are.

The functions associated with feature extraction and association will be discussed in relation to seven tasks: (1) signal parameter estimation (extraction of lowest-order features), (2) screening, (3) early classification based on especially distinctive lower-order features, (4) association of lower-order features into appropriate higher-order features, (5) alerted searching for undetected lower-order features based on expected associations, (6) association of higher-order features with targets, and (7) classification based on especially distinctive higher-order features.

7.1 *Signal parameter estimation (extraction of lowest-order features)*. . . .OIR: 6

In order to support the target localization, motion analysis, and classification functions, appropriate features must be extracted from received signals. The features of interest can be considered random variables, and therefore their characteristics will be derived in a statistical sense.

However, the probability distributions of the variables of interest often are not stationary; typically they exhibit both time and space dependencies. Therefore, each of the extracted statistical parameters must have associated with it the time for which it was derived and an appropriate spatial specification. The more radically the probability distributions of the signals of interest depart from stationarity, the more they approach what we characterized earlier as "transients"; in that case they present a situation in which non-stationary behavior may represent very important information that may be difficult to automatically characterize. In contrast, the characterization of random variables that have stationary probability distributions, by

means of automated feature extraction techniques, is a problem that may be approached with some confidence. It has been shown that a machine can exceed man in the precision of such extraction.

However, the problem of adequately characterizing radically non-stationary processes automatically can be approached with much less confidence. Substantial efforts and some progress have been made in this area, but we do not believe that it has been demonstrated that machines can presently equal the capabilities of man in adequately extracting, characterizing, and utilizing these kinds of features.

7.2 *Screening.* . . . . OIR: 6

Based upon signal parameter estimation, it can usually be concluded that certain signals do not require further immediate attention. Examples of such signals are equipment- or platform-generated artifacts or artifacts associated with the transmission medium, signals which have already been accounted for, and signals that have not yet been accounted for but which are not believed associated with targets requiring immediate attention.[2]

7.3 *Early classification based on especially distinctive characteristic lower-order features* . . . . OIR: 2

Certain targets may produce especially distinctive signals which lend themselves to automatic detection and consequent early classification. However, such classifications are not very often certain because of probable overlap of attributes of targets from different classes.

7.4 *Association of lower-order features into appropriate higher-order features* OIR: 8

The basic parameters of a signal can often be interrelated in such a way as to draw inferences about the physical features or behavior of a target. These in turn lead to probability statements about

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[2]Certain unchanging artifacts, characteristic of a specific system, may actually be screened out during stimulus processing, reducing the processing load during the detection and feature extraction functions. However, there remains a significant subset of the total stimulus set which is dynamically changing and therefore cannot be eliminated during early processing.

the target's nature. This is a classic problem in pattern recognition, the solution to which is very difficult to automate, particularly when the signal space is occupied by many targets at a given time. At this stage of development, man's role in these processes remains critical.

7.5 *Alerted searching for undetected lower-order features* . . . . OIR: 2

Once tentative identification of a signal pattern is made, one may predict the appearance of other pattern elements even if they are not initially detected. Knowing the characteristics of these undetected pattern components permits alerted search for the remainder of the pattern, likely by refocusing system attention.

7.6 *Association of higher-order features with targets* . . . . OIR: 8

This activity consists of associating together all higher-order features that appropriately belong to a particular target and carefully excluding features that belong to other targets, so that proper classification of the target can take place. The task is made difficult by the simultaneous presence of many signal sources and overlapping target characteristics. Again, the pattern recognition capabilities of man appear essential for success. It is significant to note that many potential clues to target association have been omitted in the various attempts to automate this task. It is therefore not surprising that no attempt at automated target association that we know of will function adequately in a stimulus-rich environment.

7.7 *Early classification based on especially distinctive characteristic higher-order features*. . . . . OIR: 2

Somewhat infrequently, a distinctive combination of target features, derived from a combination of lower-order signal features, will permit classification of the target with high confidence. The emphasis is on *especially distinctive*, which permits automation to be more successful in this case than in others where the pattern to be recognized is less obvious.

8. *Feature space transformation*. The goals of feature space transformation include reducing the dimensionality of feature space to reduce system information processing

load; increasing discriminability so that classification can be done in the feature space which yields the best results; and, sometimes, coordinate transformation, for example, to describe target location and motion in an appropriate coordinate system. The crucial factors involve discovering appropriate transformations, particularly since dimensionality reduction and discriminability enhancement are often inversely related.

With respect to man-machine function allocation, transformation of features to reduce dimensionality and maximize discriminability is something of a gray area. If man is acting as the principal feature extractor/associator, he will perform some feature space transformations on his own. To the extent that some of the following tasks are automated, however, they may involve further feature space transformations by computer algorithm.

Feature space transformation will be described in terms of three tasks: (1) combination of features to reduce dimensionality, (2) combination of features to maximize discriminability, and (3) coordinate transformation.

8.1 *Combination of features to reduce dimensionality.* . . . . OIR: 5

As might be inferred from our discussion of the feature extraction/association function, an extensive analysis of surveillance system stimuli can lead to a quite large number of features of various types and diagnostic potential. The independent processing of all these features during subsequent downstream functions may burden the system with an undesirable or even impossible load, and it is therefore almost always desirable to apply some transformation to the feature space as it is originally extracted so as to reduce its dimensionality. The simplest technique for doing this, which is absurd, is to omit features randomly until the processing load is reduced to a tolerable or desirable level. It is easy to demonstrate that machines do not do this, rather, that programmers do not design feature space transformations in this way. It is not so easy to demonstrate that human operators do not occasionally do this. In any event, if omission is to be the technique of dimensionality reduction, it is obviously more sensible to be selective in picking what is to be omitted. In system design stages, this is sometimes accomplished by omitting the features that are most difficult to extract, leading to a calculated failure to extract them at all. While this may be justifiable on the grounds of cost or technical constraints,

many of the shortcomings of automation in surveillance systems can be traced to the omission of such features.

Another, more desirable way to reduce dimensionality is to use a linear combination of features, wherein the coefficients are allowed to take on appropriate values according to the diagnostic potential of the features. One is not limited to a linear combination of features. The combination may be more complex. It is easy to imagine, for example, that feature space transformations that occur within human operators may be quite difficult to define in simple mathematical terms. Regardless of the mechanism, the goal of dimensionality reduction is almost always tempered by the concern to conserve information and maximize discriminability.

8.2 *Combination of features to maximize discriminability* . . . . OIR: 5

The appropriate combination of features to maximize discriminability is not easy to specify. Coupled with the need to reduce feature space dimensionality, arriving at an appropriate means to combine features becomes a problem of magnitude second only to extracting features in the first place. If we consider feature space transformations that can be executed in computers to reduce dimensionality and maximize or minimize the loss of discriminability, we can define what is going on, if not demonstrate that what is going on is optimal.

For example, in a multivariate discriminant analysis approach, the weights or coefficients to be used in the linear combination of features for the construction of each dimension in a new feature space are derived from the components of the eigenvectors resulting from the solution of an eigenvalue problem so structured that between-class distances are maximized with respect to within-class dispersions. Naturally, the example target classes which serve as a data base for the eigenvalue problem, or for any other approach to feature space transformation, must consist of a very substantial and representative library of actual target signals of various classes from which the features to be transformed are to be extracted. To the extent that various target class dispersions in the original feature space conform to the assumptions of the particular technique being used (for example, the assumption of multivariate normal distributions, the equality of dispersions

among all target classes, or whatever), multivariate statistical techniques may provide optimum solutions to the weighting of the various features for the purpose of transformation to a space where dimensionality may be reduced while minimizing loss of discriminability (e.g., by omitting dimensions with the smallest associated eigenvalues).

8.3 *Coordinate transformation*. . . . . . OIR: 1

Certain features extracted in the course of surveillance system functioning need to be transformed to more convenient or appropriate spaces in a perfectly obvious and well-defined mathematical manner; it seems clear to us that such transformations should be done by machine.

9. *Target localization*. The goal of target localization is to determine target position parameters in physical space with sufficient speed and accuracy. Crucial factors include system resolution in physical space and the ability to track moving targets. Target localization requires precise estimation of certain parameters, difficult for man to accomplish, and a large variety of mathematical computations. This function therefore is particularly suited to automation.

The target localization function is described in terms of three tasks: (1) single-sensor fixing, (2) multiple-sensor fixing, and (3) tracking.

9.1 *Single-sensor fixing* . . . . OIR: 2

The simplest case of single-sensor fixing involves target localization using an omnidirectional sensing device. Omnidirectional sensors do not furnish azimuthal information. However, if such a sensor has limited range capability, it can provide a useful circular area of probability within which the target might lie. In systems which provide beam-forming, target azimuth may be estimated. Range may be projected to some degree if target bearing rate and speed are known or can be inferred through intelligence or other sources of information. With a single passive sensor, an estimate of target range is difficult to define with adequate precision. An active system, of course, can provide both azimuth and range.

9.2 *Multiple-sensor fixing* . . . . OIR: 2

Cross-fixing involves bearing/range determinations on the same target from two or more sensors which are

at different geographic locations. A multiple-sensor fix is generally more accurate than a single-sensor fix. An important consideration in cross-fixing is communication between machines or operators attending the various sensors. The outputs of several sensors may be brought together at a single location, in which case this communication may be done directly. If the outputs terminate at different geographic locations, complications in communication are introduced. The first requirement in cross-fixing is to ensure that the various sensors are looking at the same target. This relates to the task of associating features with targets, which can be facilitated by the correlation of information among sensors, either at the stimulus level or at some higher system output level. We will discuss this further when we take up the communication function.

9.3 *Tracking* . . . . OIR: 2

The term "tracking" denotes the problem of successfully maintaining target localization over a period of time, which is significant, and which can be aided by the approaches we cite to target localization and by the various methods of determining target motion parameters discussed beneath that function. Successful tracking provides an input to target motion analysis, and successful target motion analysis, which has inputs other than position-versus-time analysis, will aid in successful tracking.

10. *Target motion analysis.* The goal of target motion analysis is to determine target motion parameters with sufficient speed and accuracy. The crucial factors include system resolution in physical space and in other target motion-related feature dimensions (e.g., doppler shift) and the ability to track moving targets. Target localization, target motion analysis, and the ability to track moving targets are all closely related.

However, we feel that localization and motion analysis are sufficiently different that each deserves a place on our list of functions. Tracking is accomplished *de facto*, when localization is successfully maintained over a period of time. We have listed "ability to track" as a crucial factor in localization and motion analysis in the sense in which it reflects a system's tolerance to changing parameters.

We would expect a human operator to review the outputs of automated localization, tracking, and motion analysis algorithms, because the experienced operator develops

insights regarding system functioning and probable target behaviors that can permit detection of errors in the automatic execution of these tasks.

Target motion analysis is considered in terms of three tasks: (1) inference of motion based on extracted stimulus features, (2) position-versus-time analysis, and (3) track aiding.

10.1 *Inference of motion based on extracted stimulus features*. . . . . OIR: 2

Some stimulus features relate directly, or indirectly, to target speed. Analysis of these features, together with knowledge of target class, makes possible inferences about target motion.

10.2 *Position-versus-time analysis*. . . . OIR: 2

Successive localizations of a target over a sufficient period of time serve to indicate target motion parameters. Currently, position-versus-time analysis is conducted in some instances manually. However, we believe that this task, and most of the others listed under target localization and target motion analysis, are obvious candidates for automation, because solutions can be achieved with greater speed and accuracy. The use of automation is growing, but we feel that there is room for broader application.

10.3 *Track aiding* . . . . OIR: 2

As mentioned above, the results of target motion analysis are useful in target localization. First, knowing target motion parameters permits prediction of a track, assuming the parameters do not change. Second, the nature of motion parameter changes may sometimes be inferred from changes in lower-order features of the signal, before the target departs noticeably from its predicted track; this may enable more timely modification of the track.

11. *Classification*. The goals of the classification function are to determine *what* a target is, what it is *doing*, and *why*, with sufficient speed and accuracy. Much attention has been focused upon this function, and some of the crucial factors relating to it, put into decision-theoretic terms, are: knowledge of target class likelihood functions in appropriate feature spaces; knowledge of *a priori* probabilities; knowledge of decision risk functions; knowledge of appropriate decision rules;

and the capability to execute logical decision processes. The execution of the classification function typically places heavy demands upon the memory function.

Classification is a decision-making function. There is a large and rather bewildering body of literature regarding the decision-making behavior of human beings (see Rapoport and Wallsten [1972]). Here we shall only attempt to paint with a broad brush the outlines of human decision behavior as we feel they apply to classification in surveillance systems.

Classification depends upon adequate execution of the feature extraction/association function. Man is generally superior to machine in performing most aspects of that function. However, to successfully employ the extracted features, the classification function calls for appropriate and sometimes complex aggregations of these features and requires comparison of these aggregations to very large amounts of information held in some form by system memory. Now, man as a logical processor is known to be somewhat faulty; man as an information storage device is also less than perfect. These characteristics of man almost certainly impair his performance of the classification function to some degree.

We suggest that there are two approaches which, taken either independently, or preferably, together, should improve system functioning. First of all, we have no doubt whatever that man's classification performance could be substantially improved by the appropriate selection, training, and motivation of surveillance system operators. Second, we feel that the logical processes involved in the classification function are suitable candidates for automation. We are inclined to believe that a combination man-machine approach to the classification function could bring about substantial system performance improvements.

Two things are worthy of mention at this point regarding our discussion of classification. First, the reader will notice a flavor of decision theory in our organization and description of various classification tasks. We think decision theory provides an appropriate framework within which to structure a description of classification, but we have attempted to maintain sufficient generality so that our discussion may apply equally well to the tasks as they are executed by men or various kinds of machines, at least in the sense of a *model*. Second, not *all* the following tasks will necessarily be

executed by a human operator or a machine for a given classification problem; some of them may rarely be executed, and some of them may not even be within the repertoire of behavior of a particular system. Nonetheless, to maintain adequate generality, we feel it necessary to touch upon each of the following tasks in turn.

The classification function will be discussed in terms of eleven tasks: (1) determination of stimulus source likelihood estimates, (2) alerted searching for undetected signals typically related to inferred stimulus sources, (3) determination of stimulus source configuration likelihood estimates, (4) determination of operating behavior likelihood estimates, (5) determination of target class likelihood estimates, (6) alerted searching for undetected signals typically related to inferred target classes, (7) determination of target class *a priori* probabilities, (8) determination of target class *a posteriori* probabilities, (9) determination of classification decision risk functions, (10) determination of an appropriate decision rule, and (11) classification decision making.

11.1 *Determination of stimulus source likelihood estimates* . . . . OIR: 5

This task may be defined as estimating the likelihood that a particular signal characteristic would be produced by a particular physical source. It may be executed in a number of ways, for example, by stimulus matching techniques, by multivariate statistical analysis, or, in the case of the expert operator, by recognition. In any event, the task will place heavy demands upon the system memory function, which in some form or other must store the necessary technical intelligence information, in addition to the task algorithm.

11.2 *Alerted searching for undetected signals typically related to inferred stimulus sources* . . . . . OIR: 2

The physical sources thought likely to be responsible for certain stimulus components that have been detected may be known to commonly produce other components that have not yet been detected. In that case, an alerted search for these undetected components may be initiated.

11.3 *Determination of stimulus source configuration likelihood estimates*. OIR: 4

This task is similar to 11.1 but involves relationships between the signal characteristics and various

characteristics of targets rather than a direct relationship with target type itself. Thus the inference of target type is more remote.

11.4 *Determination of operating behavior likelihood estimates*. . . . . OIR: 7

By "operating behavior," we mean the answer one would hope to be able to give to the question, "What has this target been doing?" This is an important question to answer correctly, because that answer can help considerably in answering the key question, "What *is* this target?" And, when both of these questions can be answered, it sometimes becomes evident *why* the target is behaving as it is. Expert operators infer operating behavior from target histories all the time, and put those inferences to crucial use in answering the critical classification questions of surveillance systems. Programming a computer to do the same thing can be a formidable task.

11.5 *Determination of target class likelihood estimates*. . . . . OIR: 3

This task consists of estimating the likelihood that target signal "i" would be produced by a target of class "j" for all appropriate "i" and "j." The target classes under consideration may be very broad categorizations, such as threat and non-threat, or they may represent more specific types. The determination of target class likelihood estimates may be based upon any or all of the preceding tasks we have discussed under classification, or it may be based upon some sort of Gestalt technique which does not explicitly involve the preceding tasks in any obvious way. However it is executed, the task of determining target class likelihood estimates is without doubt one of the most important in surveillance systems, and it is the task in which all the other stimulus-related functions and tasks culminate. It also requires very substantial support from the system memory function to permit the association of target signals of unknown origin to the known characteristics of targets of various classes.

11.6 *Alerted searching for undetected signals typically related to inferred target classes* . . . . . . OIR: 3

Once it is inferred that a signal may be generated by a certain class target, it can be determined

whether it contains all the components typically generated by that class. If it does not, an alerted search may then be initiated in an attempt to detect the missing components.

11.7 *Determination of target class* *a priori probabilities* . . . . OIR: 4

Target class likelihood estimates as we have defined them are derived solely from sensor stimulus data (along with necessary supporting information) without regard to the relative frequency of occurrence of targets of various classes, or with respect to the prior probabilities of detecting targets of given classes based on any other considerations. The determination of *a priori* probabilities in our structuring of the classification function is reserved as in independent task, which we are now defining. Estimates of *a priori* probabilities for target classes and their behaviors may be based upon information derived from other sensors or other sources of intelligence. For example, it may be known that a target of a given class is "tracking" in such a manner that it will probably be detected by a given surveillance system, leading to a rather high *a priori* probability. The derivation of *a priori* probabilities usually involves a component of subjective evaluation by some human judge, during programming and/or in real time.

11.8 *Determination of target class* *a posteriori probabilities*. . . . . OIR: 2

In this task, the target class likelihood estimates are combined with the target class *a priori* probabilities (hopefully, with Bayes' rule) to derive *a posteriori* probabilities that a target of class "i" is actually producing target signal "j," for all appropriate "i" and "j." These probabilities will be utilized in the decision-making tasks which follow, but their values are of considerable independent interest and may be reported along with the results of actual classification decision-making, since they serve as indicators of confidence regarding the final decision and possible alternative decisions.

11.9 *Determination of classification* *decision risk functions* . . . . . . OIR: 3

This task must rely upon the executive and memory functions, and appropriate inputs thereto, to derive

estimates of the "risks," "costs," or "utilities" of the various possible target classification outcomes. In many instances these will be estimated in a highly subjective manner, and sometimes quite inappropriately.

11.10 *Determination of an appropriate decision rule* . . . . OIR: 2

An appropriate decision rule must be selected to come to a classification decision. Various decision rules might be employed, such as a "maximum likelihood" rule, in which the target will be assigned to that class which shows the highest *a posteriori* probability; or, in an even more rudimentary scheme, to that class which has the highest likelihood estimate, thus ignoring the *a priori* probabilities; or, rules which consider the risk functions, such as Bayes' rule, which permit minimization of the expected risk or cost, where the *a priori* probabilities are reasonably well-known; or Minimax rules, which minimize the maximum conditional risk, where the *a priori* probabilities are less certain; or, a Neyman-Pearson rule, which attempts to maximize the correct classifications while holding the false alarms to some preset value which is determined either implictly or explicitly from cost and *a priori* probability considerations. In automated decision-making systems, the rule or rules employed will obviously be uniquely identifiable; when man is the decision-maker, it will not be so easy to determine what rule or rules are operating.

11.11 *Classification decision making*. . . OIR: 3

Based upon the foregoing tasks, decisions may be made as to what a target is, what the target is doing, and why the target is doing it. Depending upon the nature of the target's signal and the quantity and quality of the information and algorithms necessary to support the foregoing tasks, these decisions will be made with varying degrees of confidence. The output of this task is crucial. It is the *raison d'être* of surveillance systems.

12. *Communication*. The goals of this function are to provide channels to permit coordinated surveillance system operation, to convey surveillance system outputs to external agencies, and to receive instructions and other information from external agencies. The communication function is subject to constraints upon encoding/decoding, speed, accuracy, reliability, and channel bandwidth.

Ideally, the development, formatting, encoding, transmission, decoding, interpretation, storage, and retrieval of messages necessary to achieve integrated system functioning must occur in as timely, smooth, and error-free manner as possible. The communication function as it is often executed is archaic. Men are involved in all sorts of information handling tasks that, given the potential of present-day technology, they should not be.

The communication function can be broken down in terms of three tasks: (1) system coordination, (2) system output, and (3) system input.

12.1 *System coordination* . . . . OIR: 3

The functions and tasks of detection, feature extraction and association, localization, target motion analysis, and classification require or are greatly facilitated by the coordination of information from various sensors. Ideally, the network of surveillance systems of all types should be so well integrated that they might be regarded as representing a single species of surveillance system. Consequently, one of the most important portions of the executive control function could then be devoted to the centralized control of the integrated system. However, successful execution of integrated control depends heavily upon the communication function.

12.2 *System output* . . . . OIR: 3

Surveillance systems exist to provide strategic, tactical, and technical intelligence to user agencies. The user agency may or may not be closely linked with the operating agency. In any event, the communication function must provide system output to the user agencies in an accurate and timely manner.

12.3 *System input*. . . . . OIR: 3

User agencies may make inputs into a surveillance system to alert the system to the possible presence of targets, to request increased attention to targets that are present or are likely to be held by the system, and to provide intelligence information from other sources that may enhance system performance. Inputs from user agencies are obviously very important, since surveillance systems exist to serve those agencies. Both system input and output appear to be candidates for considerable automation.

13. *Learning*. The effects of learning should be twofold. First, they should result in modification of system behavior in such a way as to improve performance. Second, they should reveal new or changed target characteristics or targets to improve strategic, tactical, and technical intelligence. These results are closely related. Functionally, systems learning is embodied in modifications to the system memory function. This applies to both man and machine, and can come about internally, in adaptive systems, or through reprogramming by an external agency.

The learning function is broken down into four tasks: (1) strategic and tactical intelligence, (2) technical intelligence, (3) system operational characteristics, and (4) training.

13.1 *Strategic and tactical intelligence* OIR: 5

A surveillance system exists to obtain strategic and tactical intelligence, which is sent to the user agencies. However, this information should also be "learned" by the system, by feedback to the system memory function, so as to improve surveillance system performance as new information is acquired.

13.2 *Technical intelligence*. . . . . . . OIR: 5

The surveillance system acquires and provides user agencies technical intelligence regarding target characteristics. However, this intelligence is the cornerstone upon which successful system functioning is built. Therefore, new technical intelligence should also be incorporated into the system to enhance functioning. Any technical intelligence provided to the system from outside agencies should be incorporated as well.

13.3 *System operational characteristics*. OIR: 5

One cannot precisely know until a system is fully operational all the nuances of man-machine-task interaction that will be required for effective system operation. As the system operates, system operational characteristics of a very detailed nature become evident. These lead to understanding of system strengths and weaknesses and can be utilized to enhance system performance.

13.4 *Training*. . . . . OIR: 5

In adaptive systems such as man and some machines, the results of the three preceding tasks are automatically incorporated into the system memory function, hopefully in a way to improve system performance. However, both men and adaptive machines require a certain amount of training or reprogramming to ensure that the right things are incorporated into system memory as a function of system experience.

CHAPTER 3

A MODEL OF HOW MAN FUNCTIONS IN SURVEILLANCE SYSTEMS

There are two fundamentally different sources of knowledge concerning man's functioning that should be of importance to designers of surveillance systems. The first has to do with his observable performance, that is, how well he actually performs the tasks that are assigned to him. This evidence takes the form of such experimentally measurable outputs as level of alertness (vigilance); target detection performance; accuracy of feature extraction/association, target tracking, localization, and classification; communication skills; and various interactions with the machine.

A considerable body of information is presented in Volume II of this report concerning the actual performance skills of operators in different types of surveillance systems. In this volume, we will confine ourselves to a second source of knowledge concerning man's functioning. This takes the form of a model of human information processing and it will be evident that the operator performs as a kind of specialized surveillance system in his own right.

It is emphasized that a treatment of this second kind of unobservable, internal behavior relies heavily on theory and laboratory experimentation. Thus, the model which follows is a distillation of some key theoretical concepts from psychology and physiology that we feel are relevant to an understanding of human information processing in surveillance systems. The model does not represent any single viewpoint; it is an interpretation and synthesis that will provide some foundation for the systems designer to apprehend a subset of research that is relevant to human operators in surveillance environments.

Some of the components of the model have been well demonstrated in laboratory studies, some have been strongly implied from laboratory research and through observations, and some components of the model are theoretical constructs necessary to link other components to one another and to explain certain aspects of human performance.

We wish to emphasize that this is a functional model; the components are not necessarily homologous with the physiological mechanisms that must underlie human information processing, since the *exact* mechanisms underlying this kind of behavior are not known at this time.

The Model in Brief

Figure 3.1 shows the functional model of human information processing. The model posits that as the *stimulus environment is scanned*, images are stored in *temporary buffers; features* are then *extracted* from the sensory images before the image decays. By features, we mean a set of descriptives that include, as well, the relationships among descriptives.

The model shows *preliminary processing in memory* before a given feature set impinges upon human *consciousness*. The so-called "cocktail party phenomenon" is an example of this preliminary processing: While one's attention apparently may be devoted to a single conversation during the cocktail party, some rudimentary parallel processing of other conversations is occurring, because one can immediately switch channels when his name is heard coming from one of the "unattended to" conversations. The mechanism for explaining this includes a *pertinence function* which biases the preliminary processing and attaches priorities to various stimuli or feature sets.

The result of the above processing is that certain features are selected for greater attention and, conversely, other features are rejected and do not come under scrutiny of consciousness.

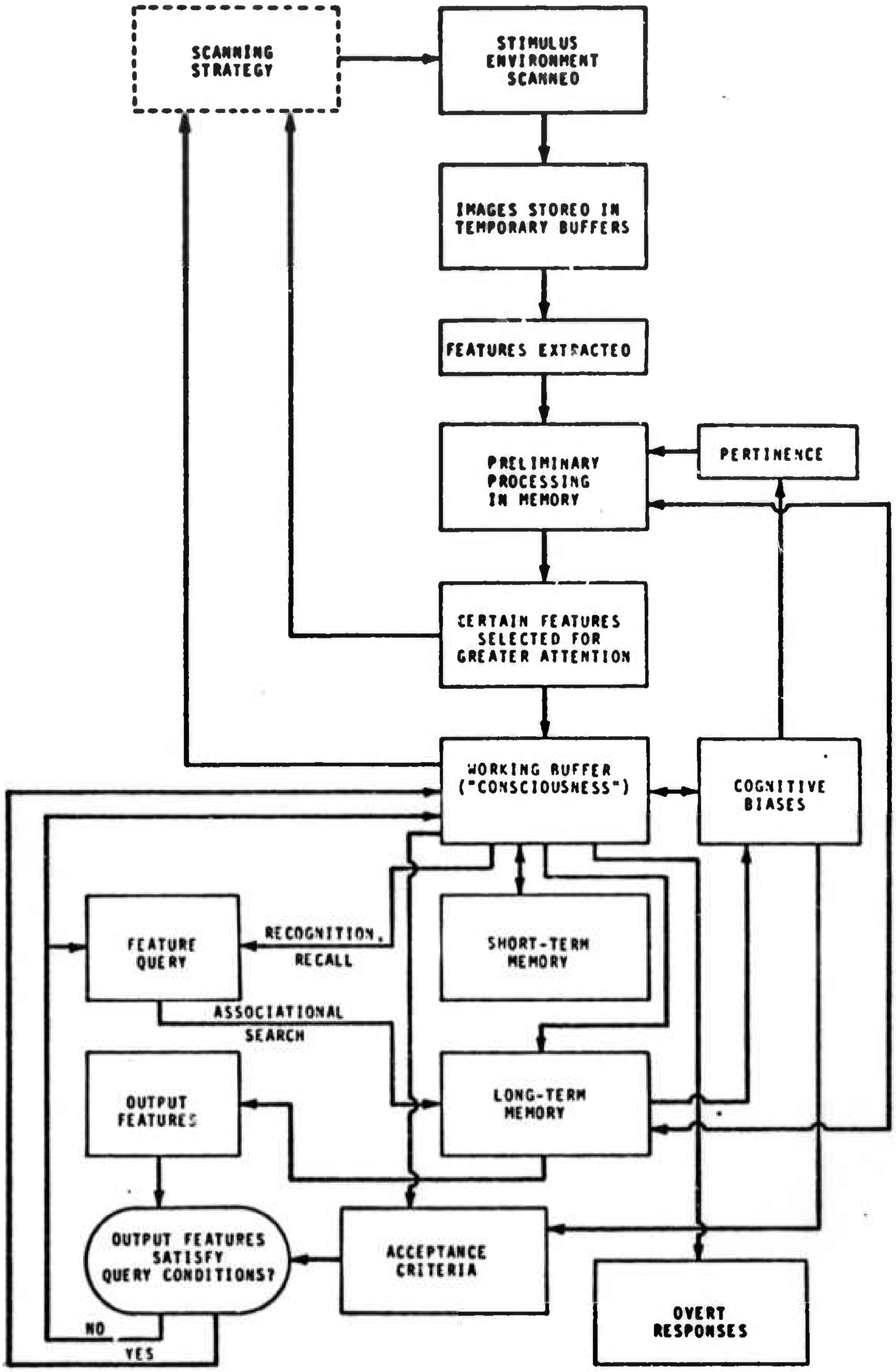

Figure 3.1. Functional model of human information processing.

An instantaneous, *working buffer*, which we may call *"consciousness,"* is postulated. In this working buffer, the human has great opportunity for exerting some sort of control over the other aspects of his information processing system: He may direct his *scanning strategy;* as we shall see later, he may instigate rehearsal and other procedures for ensuring that items are retained in *short-term memory* or that they are transferred to *long-term memory;* he may adjust his *biases* so as to affect *pertinence* and therefore shift his attention; and he may, to some degree, direct his *recognition* and *recall* activities.

Closely linked with the working buffer is a *short-term memory* store which will retain information for approximately 30 seconds. This storage provides the immediate and highly interactive link between the working buffer and memory that is needed to maintain continuity with ongoing tasks and the stimulus environment. Information that is more permanently stored resides in *long-term memory,* and this information is not as accessible as that in *short-term memory.*

The reader will recall that this is a functional model, not a physiological one. This is particularly true in the case of *short-term* and *long-term memory;* the distinction is a functional one and, although a large amount of experimental evidence reveals the distinction between the characteristics of information storage in *short-term memory* and that in *long-term memory,* it is not at all clear that these two memories occupy different neurophysiological locations. It may rather be that there are differences in the organization and accessibility of different kinds of information stored in a single location.

Whatever the physioloigcal differences or similarities between *short-term* and *long-term memory,* it is clear that information is less accessible in *long-term memory.* For certain kinds of *recognition* tasks or the *recall* of previously learned

information, it appears that consciousness creates a *query* and *associational search* of *long-term memory;* and the output of the search is subsequently tested. If *recognition* has indeed taken place, or the desired information *recalled,* the process is terminated and *consciousness* becomes aware of the result. If the search has been unsuccessful, a new search may be initiated with the *query* modified to take advantage of any associations retrieved from the prior search.

This subsystem may be influenced by a function we have labeled *acceptance criteria.* Often we are confronted with a partial pattern that we subsequently "recognize" even though it may not contain all of the features we have learned to associate with that pattern. For example, a two-dimensional, black and white photograph of a familiar face usually passes the acceptance criteria even though it contains only a subset of the features normally defining that face.

A component in the model which directly and indirectly influences many aspects of human information processing has been labeled *cognitive biases.* Webster defines "cognition" as the process of knowing or perceiving. Psychologists use the terms "cognition" and "cognitive" to refer to the kind of human information processing under discussion in this document; sometimes "cognition" is used by psychologists to include "thinking" and other hard-to-define topics like "awareness." We have used the term, in conjunction with "bias," to create a convenient mechanism to describe how past and present experiences influence perception of current stimulus inputs and recall of past information stored in memory. The *cognitive bias* mechanism is really a part of memory, but it is extremely useful to separate it from our main treatment of memory in order to focus upon certain peculiar human phenomena, to be discussed later.

The final component in the model represents the *overt responses* which may be empirically observed. With few

exceptions, most of what is known about the internal workings of human cognition has been inferred from studies where scientists manipulate stimulus input to human subjects and carefully measure the output in the form of overt responses. The model does not discuss the many types of overt human responses, but Volume II of this report addresses those aspects of human responses relevant to surveillance systems.

Various elements of the model will now be described in more detail with specific comments on the strengths and weaknesses of human operators with respect to the various functions.

Memory

Investigators in the area of memory are fairly well agreed that there are three basic types of memory:

1. Temporary buffers

2. Short-term memory

3. Long-term memory

The *temporary buffers* represent the first and most transient element of memory store. These contain fairly literal representations of the stimulus environment. The transient memory has been called *iconic* and *echoic* memory for visual and auditory images respectively. That is to say, an *icon* or exact visual representation seems to be stored in this memory, and an *echo* or exact auditory representation seems to be stored in this memory.

The iconic memory subsystem stores something analogous to "snapshot" of the stimulus pattern. This snapshot decays rapidly, in about one second. The operator can extract information from this decaying memory for as long as it is available. Echoic memory is also quite short. Various experiments have shown that the echo, which has not been extensively coded but is, rather, a high fidelity representation of the impression that the physical stimulus makes upon the sensory system, persists for about two to ten seconds.

There is nearly unanimous agreement on the existence of two types of relatively durable memory in human operators, *short term* and *long term*. The short-term memory store may maintain a given feature set for about 30 seconds, and the long-term memory store maintains information for much longer periods of time. Indeed, some investigators feel that long-term memory is permanent; however, interference from more recent associations and learning experiences makes access to older material more difficult. Other investigators feel that information may slowly decay from long-term memory. A very few investigators feel that there is no qualitative difference between short-term and long-term memory and that the two memory systems actually represent the ends of the continuum of a single-memory system that shows loss of information as a result of time and certain other conditions. This latter viewpoint, however, is not consistent with certain neurological evidence.

In addition to their relative duration, another way of distinguishing between short-term and long-term memory is by their relative capacities. The capacity of short-term memory is approximately seven items where an item may be a letter, a number, a word, a string of numbers, etc. The number of items that can be contained in short-term memory is surprisingly constant although the amount of information represented by the seven items may be variable from an information theory point of view.

The capacity of long-term memory, as is intuitively obvious, is much, much larger, and the absolute capacity, in terms of items of information stored is exceedingly large.

In contrasting the memories of men and machines, one must be impressed with the extraordinary storage capacity of human memory. It may well be that any item that is passed from short-term into long-term memory is, in some sense, permanently stored. Man's extremely rich memory provides him

with a capability for rapid recognition of many patterns of information, including degraded patterns, that are important for surveillance system operation. However, the efficiency of man's memory *retrieval* depends upon degree of initial learning, the frequency with which the information is retrieved, and many other variables. Whether or not man's memory decays in the sense that information is actually lost, or whether retrieval from memory storage simply becomes more time-consuming and difficult when the information is rarely used, is a moot point. There seems little doubt man's memory systems exhibit both less reliable storage and less reliable retrieval than does the memory of machines and thus are highly significant areas for computer aiding in an optimum man-machine design.

Attention

The elements of attention as reflected in the model include the following functions:

1. Image storage in temporary buffers
2. Feature extraction
3. Preliminary processing in memory
4. Selection of certain features for greater attention
5. Pertinence evaluation

We have remarked upon the function of the temporary buffer; it contains a high fidelity representation of the stimulus environment. This representation decays very quickly and/or it is overlaid with new material. During the time in which the representation remains viable, features are extracted from it. Undoubtedly this feature code is complex; it represents descriptive features plus the relationships between features plus the relationships between relationships, and so on.

The next point in the flow of information is critical for an adequate model of attention. All of the features which are extracted are subjected to some sort of preliminary processing that discards most of the features as uninteresting and retains a few to be presented to consciousness as the stimuli for immediate attention. It is perhaps this characteristic of human attention that differentiates it most from comparable functions in machines. The process is largely automatic; it does not require an act of volition. According to the model, certain features of the stimulus environment have high *pertinencies* attached to them and, during the preliminary processing, result in attention being focused on them. In other cases, the pertinence of a feature may or may not be sufficiently high to warrant that feature entering consciousness.

The notion of differential pertinence for different features of a stimulus pattern has obvious application in surveillance systems. The operator who efficiently detects a threat target has a very high pertinence associated with certain features of the displayed signal. A casual glance at the information display may result in immediate focus of attention on those features if they are present. At the same time, he apparently does not attend to most of the features that represent uninteresting target signals. The pertinence function provides more than a convenience in filtering out certain features; it appears to be an absolute necessity, for men do not appear to be capable of consciously attending to all of the features of their immediate stimulus environment.

We wish to digress at this point to examine a popular fallacy in man-machine comparisons. Often it is said that the computer is a fast processor, while the man is slow. It *is* true that men are generally slow at sequential operations, like arithmetic computations, and computers can be made to perform these tasks extremely quickly and accurately. However, this is not equivalent to saying that man is a slow processor

and that computers are fast. If one reflects on how man scans his visual stimulus environment and immediately recognizes innumerable patterns of information with different levels of pertinence for his purpose at the moment, it will be clear that he is an exceedingly fast processor of certain kinds of information input. In general he is capable of processing an extremely large number of pattern features and using selective attention to focus on the relevant subset of features. In this process he efficiently rejects irrelevant features, he is relatively undisturbed by the transformations that are irrelevant to identifying the nature of the object attended to, he is highly adaptive to changing signal characteristics from the object of interest, and he is capable of anticipating and predicting certain pattern features, given other features. In contrast, machines are generally much less adaptive than man to changing signal and environmental characteristics. The machine is highly dependent on prior definitions of signal characteristics and is usually strongly bound to previously specified instructions (although some degree of adaptation may be possible). There is perhaps no other single area of difference between men and machines that so importantly affects the critical processes associated with pattern recognition, feature extraction, and target classification.

Recognition and Recall

We have discussed some of the properties of long-term and short-term memory: how the information is entered into these memory stores, and some of the conditions under which retrieval from these memory stores takes place. The present section focuses on the formal recognition and recall process, which is of considerable interest in surveillance operations as it is the basis for classification performance in humans.

The elements of recognition and recall in the model are:

1. The working buffer ("consciousness")

2. Short-term memory

3. Long-term memory

4. Feature query

5. Output features

6. Acceptance criteria

The model postulates that during attempts at recognition or recall, a *query* is generated. This query embodies a set of features immediately known by consciousness to be associated with the item to be recalled or recognized, for example, a particular target characteristic. A search of long-term memory is then initiated. The output of this search is a list of features associated with the query features through prior experience. Different associations may have different strengths and lead to a weighting of the output features' relationship to the query features. For example, there may be a weak association of the signal input with certain classes of targets and a stronger association with other classes.

A decision mechanism tests the list of output features against the conditions of the query. Was a classification retrieved? Is the classification correct? This latter question may be answered in two ways: First, if the weight or strength of the association between the query features and the classification is very high, the classification may be accepted immediately. Second, if the strength of the association does not pass the acceptance criterion, a tentative classification may be formed which comprises a new query that is then subjected to a new associative search of long-term memory. If it is the correct classification, this search should produce at least some of the features from the original query--that is, some representation of the target features.

If classification is not retrieved in the first search, several things may happen: Consciousness may decide that a precise classification is not necessary, that just associating the signal with the broad category "non-threat" is sufficient,

and that it should go on to other things. Or, if a more specific classification is required, the list of output features may be appended to the lsit of query features to formulate a modified query, and a new search of long-term memory may be initiated. It is not at all necessary that consciousness play an active role in initiating each iteration of this process. One can easily recall instances where a recall process has not had a satisfactory result immediately, and the whole problem is "put out of mind" indefinitely, often with the result that the correct answer presents itself at some later point.

The process we have just described may have three outcomes: It may converge upon the desired associated features on one or several passes; it may diverge, always coming up with unacceptable outputs; or it may loop, always coming up with the same but unacceptable answer.

The system, as a whole, is not constrained to dealing only with the associations resulting from searches of long-term memory. The results of the search of long-term memory may provide features or cues that will stimulate a new scanning strategy for acquiring additional features to be used in future modification of the query.

We have already commented upon the richness of man's memory and some of the difficulties he frequently experiences in rapidly extracting the desired information from it. Because recognition and recall are intimately linked with the memory function it is inevitable that man's functioning in these areas should be extraordinarily good in some respects (e.g., the nearly instantaneous recognition on the telephone of the voice of an old friend that one has not heard from for a long time), but, for some kinds of information, be subject to the deficiencies associated with slow and unreliable retrieval. It seems that man's recognition and recall of highly complex stimulus patterns is quite efficient but that his

recall of detailed facts may be cumbersome and subject to degradation with time.

A final, and most important, feature of man's recognition and recall is his ability to rapidly generate new hypotheses about stimulus patterns and new tests for evaluating these hypotheses. This is a capability that we find to be quite limited in machines and another characteristic of man that presently necessitates his continuing role made in the operation of complex surveillance systems.

Consciousness

We have placed consciousness in the model in a central position as the primary working buffer for human information processing. In a sense, consciousness is analogous to the working registers of a simple serial processor computer. Consciousness receives the output of the selective attention mechanism; it initiates certain searches of long-term memory, certain changes in cognitive biases, and, eventually, certain overt responses. Consciousness is the prime mover in decision making, a topic of considerable theoretical and experimental attention. It is slavishly dependent on input from memory, indirectly through the effects of memory upon the attention mechanism and cognitive biases, and directly through the output of associational searches. It might be said that conscious awareness is only moderately dependent upon the physical properties of the stimulus environment, for the transmission of those properties to consciousness is a function of coding transformation, filtering, and distortion resulting from the effects of the memory system upon the perceptual system. And memory is not under direct control of consciousness.

We must warn the reader that we have taken a straightforward, simplistic approach to the treatment of consciousness. There is a paucity of experimental data on the topic and therefore few guidelines for incorporating it into a model of information processing. However, it is explicit or implicit in a

very large number of theories and approaches to the general human cognitive process and the model certainly seems incomplete without it.

Cognitive Biases

This component was included in the model to represent the special effects of memory upon certain aspects of human information processing. This is a somewhat artificial component because a "black box" containing cognitive biases in no way exists as such in the flow of events representing information processing. Rather, these cognitive biases are the functional *results* of past events, as they have been preserved in the memory stores. We feel, however, that it is convenient to distinguish the effects of cognitive biases from the role that memory plays in providing recall and recognition facilities. Also, by somewhat artificially distinguishing the effects of memory in the form of cognitive biases via a separate component in the model, we have provided a reminder to system designers of certain important, if somewhat peculiar and disconcerting, information processing characteristics of the human system.

Cognitive biases have two important influences on human information processing. They actually control, modify, and distort our more or less instantaneous perception of the psychological present, and, to an even greater degree, they control, modify, and distort material that is retrieved from long-term memory, the psychological past.

Cognitive biases are themselves a result of material that is stored in long-term memory; in some cases the cognitive biases may be traced to a single past event, such as certain kinds of instructions received by an operator prior to standing watch. Or, the formation of cognitive biases may be the result of a large number of events spanning several years, as in the case of perceptual distortion due to racial prejudices.

The manner in which cognitive biases effect our perception of things is not precisely known. However, at least two

possible explanations have been put forth. Haber (1966) showed that at least some phenomena due to cognitive biases can be caused by distortions in *encoding* the stimuli for later processing. In terms of the model, this would mean that a cognitive bias would cause a high pertinence to be given to certain feature sets stored in memory. As new features are extracted from images in the temporary buffer, they are subjected to preliminary processing in memory to determine which will be selected for greater attention. At this point an error occurs--the output from the preliminary processing includes some features which received the high pertinence, but which were not part of the set of features extracted from the image.

The mechanism to account for this kind of error was alluded to earlier. Increases in pertinence are functionally equivalent to decreases in the threshold for perceiving features. A feature set with a high pertinence may be so sensitized that it will be triggered by noise input, or more likely, by a feature set bearing some similarities to the sought-after features.

A second explanation of the apparent effects of cognitive biases is that there is no effect on the perceptual process, but rather, the reporting or response process is modified by erroneous memories of what was perceived. In other words, the person perceives correctly but remembers incorrectly at the time of reporting his perceptions.

In any event, an important effect of cognitive biases is in their contribution to performance variability between humans, and to variability within performances of a single operator on different occasions. In general, the more highly controlled and structured a task is, the less opportunity there is for variability due to cognitive bias. In some cases, it may be possible to achieve very similar cognitive biases within the individuals of a group. An example of this is provided by the very small variability among surveillance system

operators in signal detection performance under the alerted conditions that usually prevail when the recognition differential of the system is being measured. The conditions of such tests produce a similar cognitive bias in all operators in the form of high expectation for the imminent appearance of a signal on their display. This situation is to be contrasted with more typical operations in many surveillance systems where there is little control over the alertness of operators or over other cognitive biases that they may have. The less structured task environment characteristic of routine operations allows much greater leeway for the effects of cognitive biases to exercise themselves differentially among individuals. Different biases govern the manner in which attention is devoted to the displays, the rigor with which recall and recognition are executed, the operator's perceptual "set," and so on.

Cognitive biases appear to be a characteristic of man for which there is no obvious counterpart in machines. The central problem is not so much that a bias may exist, but that it is difficult for others to know that it exists and in what form it exists. Since cognitive biases are a derivative of long-term memory, they can only be changed through appropriate retraining. It has been demonstrated that this can be done within the context of surveillance operations (Mecherikoff, 1974) but the problem remains that the cognitive biases of most operators remain unknown and therefore constitute a significant source of operator differences in performance.

Scanning Strategy

The scanning strategy component of the model, like that for cognitive biases, is a convenient invention that has functional utility but is not homologous with any physiological mechanism in the flow of information in the human system.

We make two fairly simple observations in connection with scanning. First, while consciousness may be (1) the recipient of only partial information from the selective

attention process, (2) the dependent of a not totally trustworthy long-term memory, and (3) the occasional dupe of cognitive biases, at least consciousness has some autonomy in deciding what it will look at or listen to. Thus it has a direct input to the scanning strategy.

The second observation is that conscious control over the scanning strategy is not complete. To some degree the perceptual process, via selective attention, guides what we see and what we hear. Thus an operator in scanning a visual display may detect a curved line in a group of straight ones. He need not consciously decide to make his scan follow the excursion of the curve; it seems that his perceptual process will simply do this for him "automatically."

There are many elements of scanning strategy that appear to differentiate between men and machines. First, machines are completely systematic scanners (or can be made to be so) while man is a relatively non-systematic scanner. Second, the programming of machines to follow a wide variety of unpredictable dynamic changes in various signal characteristics (non-stationarity) makes it difficult and expensive in terms of computer capacity to develop scanning strategies that are sufficiently flexible for all possible signal variations. Man has little difficulty in maintaining this flexibility, and it is one of his most important assets relating to feature extraction, feature association, and target classification.

Man's principal deficiency in this area, and it is an important one, is that he does *not* systematically scan the entire signal space that is presented to him. Further, he is subject to degradation in his scanning behavior as a function of monotonous, routine, watchstanding conditions. In this respect he is almost certainly inferior to machines and a system designer, who is concerned with the man-machine interface, must devote a considerable amount of his resources to this problem. Displays with extended signal histories, the use

of artificial signal injection, and the sequential illumination of different parts of the display field are a few examples of "countermeasures" for this deficiency in man.

CHAPTER 4

THE VARIABLE OUTPUT OF HUMAN INFORMATION PROCESSING IN SURVEILLANCE SYSTEMS

In the previous chapter, we presented a general model of man as an information processor. If that model described a machine instead, we would expect its various outputs (overt responses) related to surveillance operations to be highly consistent, if not always correct. The hardware and software representing the various functions described in the model should produce either identical response outputs to a given signal input or at least highly similar ones. Performance should be much the same, day in and day out (barring catastrophic failure), and the hardware and software components in one production line unit should, except for deliberate modification, be interchangeable with other production line units.

When man is the subject of the model, however, we are confronted with a very different outcome. Such functions as *long-term memory*, *cognitive biases*, *pertinence*, and *acceptance criteria* are conditioned by a large number of influences that introduce extensive variability in the overt responses of human operators. The result is that these elements of the system can (and usually do) function quite differently in different operators for reasons that will be discussed shortly. Thus, one of the dilemmas facing system design and test engineers is that the human components of surveillance systems, unlike other components built to a set of engineering specifications, are *not* interchangeable parts. Not only does the output of different operators differ, but the responses of even the same operator may be inconsistent from one operating period to the next. Indeed, operators have the capacity to contribute more variance to total system performance than any

other component of the system. Recognition of this fact has probably been one of the principal incentives to automation in surveillance systems. In fact, if any other element of the system contributed as much performance variance as the operators do, there would be immediate and intensive effort directed to the problem of increasing the reliability of that component.

Sources of Operator Performance Variability

The problem of operator performance variability is not so much the fact that it exists but that it can be so large. It is large despite the fact that both selection and training programs are clearly designed to minimize it. Figure 4.1 illustrates four major sources of operator variability; we will discuss each in turn.

Innate abilities. The selection tests employed by the Armed Forces as criteria for admittance to training as surveillance system technicians are designed to homogenize and optimize the human perceptual and cognitive abilities that are important to performance in these systems. They are also designed to maximize the probability that the candidate will benefit from (i.e., successfully master) the training curriculum. The way in which this is done is to set minimum cutoff scores on various aptitude tests so as to effectively narrow the range of individual differences in innate abilities that are presumably relevant to job performance. How effective these cutoff scores are, of course, depends upon the validity of the tests for predicting actual performance on the job. Although test validity is usually fairly well established with respect to performance in basic training *schools*, their predictive relationship to *operational* performance is often a matter that is less clearly established, partly because objective criteria of performance on the job by which test validation can take place typically are unavailable.

Training. Training in a technical school is also designed to produce interchangeable human system components. The assumption

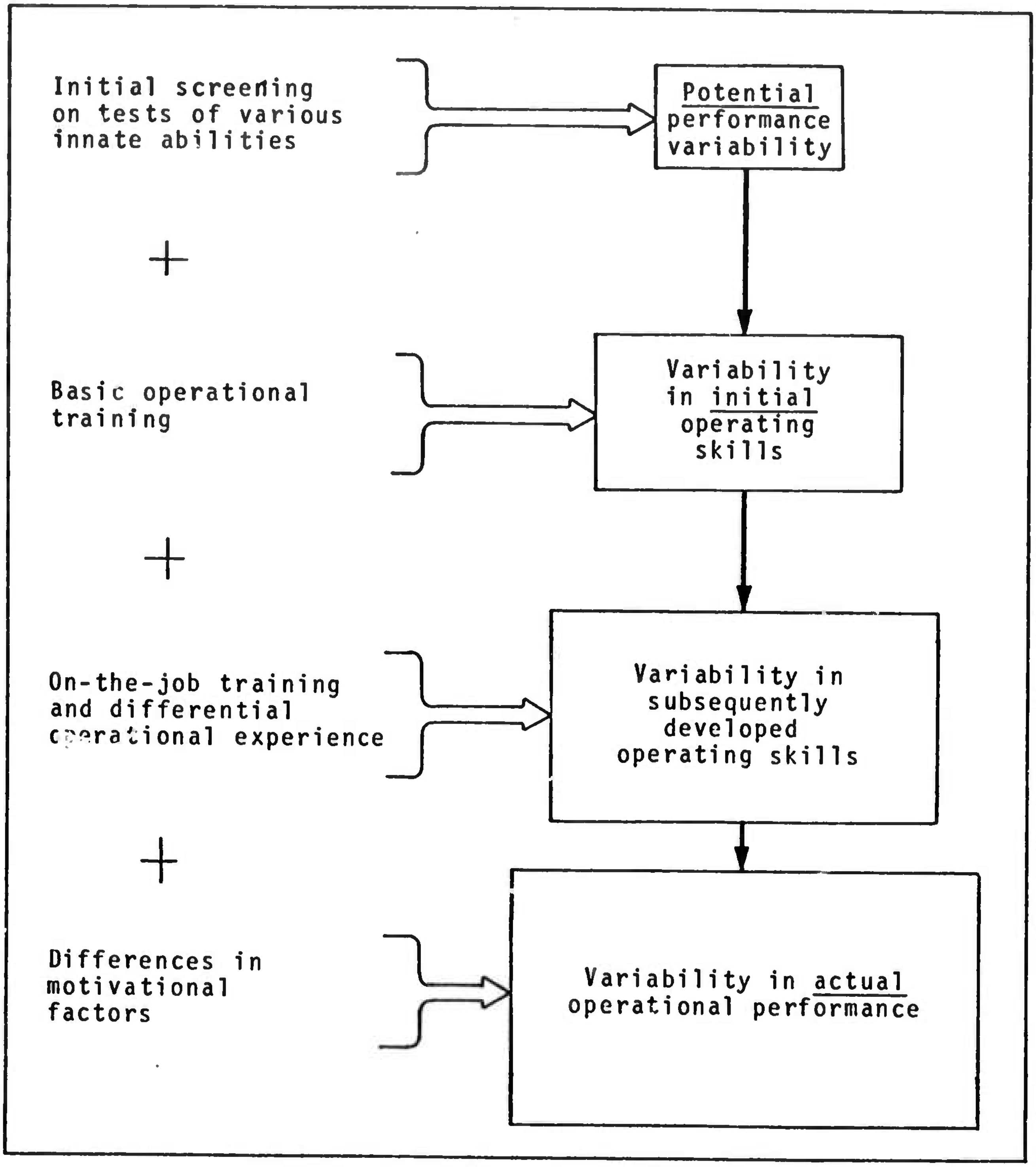

Figure 4.1. Showing increasing performance variability as a function of innate abilities, training, operational experience, and motivation.

is that anyone who has successfully completed a prescribed course of training in the operation of a particular system is generally qualified to operate that system, or soon will be, given a modicum of on-the-job experience. Explicit in the training curriculum is the objective that all students will learn to operate the system to some (usually unspecified) criterion of excellence with the hope that theoretical system capability will be achieved in practice. For some comparatively easily defined tasks where objective criteria of skill training can readily be established (for example, ability to interpret signals sent in Morse code with specified speed and accuracy), training *does* produce a relatively homogeneous product that can be plugged into an operational system and which, for a time at least, results in reasonable uniformity in systems performance. Even where such objective criteria are clearly specifiable, however, individual differences in performance soon begin to emerge. For example, within a few weeks after graduation some operators will no longer be able to perform at the school criterion level, some will still perform at about that same level, and still others will be able to perform with significantly increased speed and accuracy. Similar divergencies in performance certainly occur in the performance of the many complex tasks associated with the operation of surveillance systems, as will be clear from data presented in Volume II of this report. These performance differences reflect the fact that the selection criteria did not ensure that all personnel assigned to the school are equally able (or willing) to benefit from the training program. If the selection test scores were made sufficiently stringent so as to produce "identical" inputs to the operator training program, the resulting subset of personnel would likely be too small to meet operational requirements. Although the required caliber of personnel selected to be surveillance system operators is generally high, such personnel are in short supply; ideal selection criteria therefore must be compromised, with the

result that some unwanted individual differences are introduced into the system.

Thus, the stage is set for the development of large individual differences in performance. In spite of the fact that both selection and training programs are in some sense designed to produce interchangeable parts, the inputs to the training "pipeline" are different in various ways to begin with and these differences are magnified by virtue of differential abilities to profit from the training experience. It is important to note, however, that the personnel assignment system operates as if it *had* produced a batch of interchangeable parts. And, to a very real extent, the degree of control over the performance of the human component has been much greater to this point than it ever will be again.

Operational experience. Once an operator has been assigned for duty in an operating system, a third major variable contributing to individual differences in performance begins to show its effects. We have called this variable "operational experience," as if all operational experience were equally meaningful. But there are a number of dimensions of experience that have quite different implications for operator performance. In the case of operators of surveillance systems, certainly the most relevant and powerful determiner of individual differences in performance is the frequency and recency with which the operator has had the opportunity to detect and analyze "targets of interest" (threat or otherwise reportable targets). In most systems, targets of interest will be threat targets as opposed to non-threat types, although in some surveillance systems safety considerations may make it almost as important to quickly and accurately recognize all types of traffic.

Major sources of variety in operator experience have to do with the type of signals encountered as a result of sensor location; the type of mission assigned; procedural variables

associated with individual commands, particularly command attitude toward the importance of routine target reporting; the frequency and validity of performance feedback received by the operators; and the adequacy of on-the-job training. This variety of possible operational experiences serves further to increase performance differences among operators that already exist as a result of training differences and differences in native abilities.

Motivation. The fourth major contributor to individual differences in performance is motivation, that most important and perhaps most difficult to measure of all human traits. The consequences of motivation interact with the three variables already discussed. The impact of differential motivation at both the selection and training stages is well-known, serving negatively in some cases to produce under-achievement, and positively in others to produce performance well in excess of that expected. A most important motivational consideration in surveillance systems has to do with the operator's perception of the importance of his (frequently) very dull job and the extent to which he is able to maintain a high level of performance in the face of low expectancy for targets of interest.

It is important to note again that even after operators have had various kinds of experience, personnel assignments continue to be made as if the human components of operating systems are, generally speaking, interchangeable. Operators of a given rank and holding a particular occupational specialty code are treated as though they indeed have equivalent skills. Although advancement in rating procedures has been established that, through written tests and practical demonstrations, attempt to ensure that an operator being promoted to a particular rank meets certain specified standards of performance, the relevance of these evaluative procedures to actual ability to perform the job is sufficiently uncertain as to leave room

for large individual differences in performance skill among personnel of the same rank and specialty code.

At this point it is fair to ask, "How large are these differences in terms of meaningful operational criteria and how important are they to a designer or evaluator of a surveillance system?" A considerable body of objective data now exists concerning individual differences in many aspects of operator performance related to surveillance systems although it may not always be in a form that will be directly useful to the design engineer. The nature of the data varies with the complexity of the behavior involved. For example, there are extensive data concerning simple psychophysical relationships such as the response of the eye to various intensities and wavelengths of light, the discriminability of symbols of various sizes and shapes, and so forth. Extensive information is also available concerning the response of the ear to variour sound intensities at different frequencies, the discriminability of signals differing in pitch by various amounts, and the ability to detect signals masked by background noise. Not only are these relationships adequately described in various human engineering guides (e.g., VanCott & Kinkade, 1972), but the variability of human performance for these relatively simple psychophysical tasks is comparatively small. Thus, if we are concerned only about such relatively simple functions, the operators of surveillance systems possibly *can* be regarded as interchangeable parts, assuming they meet some minimal criteria of sensitivity.

The problem arises when one proceeds to the more complex human reactions associated with such operational requirements as feature extraction, feature association, and target classification. In each of these functions, individual differences in native abilities, assimilation of training, operational experience, and motivation combine to produce large individual differences in operator performance skills. At the very least,

it is imperative that the system designer by aware of the extent of these individual differences and, if possible, the specific reasons for them. Ideally, he will design his system so as to minimize the effects of these differences on system performance. This almost certainly means that the focus of his design at the man-machine-task level should be on those areas where human performance is known to be deficient or where operator variability is known to be large. Some of these areas are now well-known. For instance, the value of large-scale information storage and rapid retrieval systems, in aiding the operator's memory and ability to process heavy information loads, has clearly been demonstrated for surveillance systems; the development of automatic fault location systems is quite a different example, showing how computers can be used to minimize the effects of large individual differences in troubleshooting skills.

At the same time, the designer should be aware of the capabilities of highly competent operators, that is, cases of exceptional performance which can possibly serve as models for software design. From a programmer's point of view, these are (1) *unusually effective capabilities* that (nearly all) humans possess, and (2) capabilities that *unusually effective humans* possess. Since extraordinary operators, by definition, cannot routinely be furnished to operational systems, it should be one objective of the design engineer to develop software that emulates or otherwise at least equals the performance of the most highly competent operators, thus achieving the dual objective of maximizing the average level of system performance and minimizing its variability due to operator differences.

If the extraordinary operator is to be a model for future system design, it behooves the engineering psychologist to identify how that extraordinary performance comes about and, hopefully, to describe it in terms that are meaningful to

systems designers. The first step is to describe the extent of individual differences in actual operating performance. Fortunately, there is considerable evidence concerning the magnitude of these differences and some of the variables associated with them. Evidence of this kind with respect to surveillance systems is presented in Volume II of this report.

Design Consequences of Individual Differences Among Operators

The consequences of individual differences in operator performance for system design and system test are summarized below. These conclusions are generally supported by detailed data presented in Volume II.

1. The operators of surveillance systems are not equivalent or "interchangeable parts," though the personnel system generally operates as if they were.

2. Operators are likely to contribute more variance to systems performance than hardware (or software) components.

3. Command attention, procedural rules, reporting criteria, and "expectancy" for threat targets are variables that strongly influence operator performance, both with respect to target detection efficiency and reporting thresholds.

4. Selection, training, experience, and motivational variables interact so as to magnify differences in operator performance skills.

5. One objective of the system designer should be to minimize the impact on systems performance of individual differences among operators; the principal focus, of course, should be on the areas of greatest human deficiency.

6. The performance characteristics of superior operators should serve as standards of comparison for automated system functions.

7. Individual differences in comparatively simple psychophysical tasks (e.g., alerted signal detection) are small; for complex tasks they increase as task complexity increases (e.g., target classification).

8. Individual differences in ability to *voluntarily* maintain a high state of alertness are large.

9. Operators differ extensively both in ability to extract target features from the signal pattern and in their ability to relate them to the nature of the target in a logical, probabilistic manner.

10. Operators appear to be more likely to produce false dismissals than they are false alarms, whereas the opposite may be true of computer algorithms. This may be a result of the penalty for false alarms perceived by operators as a result of the higher level review necessitated by contact reports.

11. The relationship between an operator's rank and his proficiency in target detection, feature extraction, and classification is positive but small. Frequency and recency of experience with particular types of targets are considerably more important.

12. Operator performance in surveillance systems suffers from lack of feedback concerning missed opportunities and incorrect classifications.

CHAPTER 5

MEASUREMENT OF MAN-MACHINE PERFORMANCE IN SURVEILLANCE SYSTEMS

The methodology we envision for man-machine function allocation requires, in part, the empirical evaluation of man-machine performance in system configurations closely related to those being considered as design alternatives. Once a design is realized as a prototype, further performance evaluations will obviously be necessary, upon which the fate of a newly designed system may depend, and still further evaluations can be anticipated throughout the life cycle of a system, serving, in the end, as benchmarks against which later generations of systems will be compared.

Therefore, the importance of adequate systems performance evaluations can hardly be overestimated, and the presence of man in the system loop, whose variability we have attempted to highlight, has extensive implications for the experimental methodology necessary to conduct adequate systems performance evaluations. In the course of this study we observed numerous methodological shortcomings in operational evaluations that often left the outcome of the evaluation very much in doubt, despite very substantial investments in test procedures. In many cases the shortcomings were associated with a failure to consider variables associated with the human operators in the systems being compared.

A substantial experimental methodology has collectively evolved from various scientific disciplines faced with the problem of measuring relatively small effects in the presence of relatively great variability. Since the measurement of system performance with men in the loop usually poses just such a problem, an extended discussion of this methodology is contained in Volume II of this report. However, the principal points are highlighted below. Though many of them are "obvious," they are included here because they are so often violated in operational tests of surveillance systems.

1. Evaluative tests of experimental man-machine systems require comparative data from a suitable baseline (control) system, except in rare instances where absolute criteria can be specified. The necessary man-machine performance data for the baseline system usually must be collected at the same time data on the experimental system are collected because suitable records of routine man-machine performance in operational systems are rarely available.

2. Comparative tests of experimental and currently operational systems must take into account operator and procedural variables that contribute to total man-machine performance, as well as differences in hardware or software.

3. Understanding the variables related to man-machine strengths and weaknesses in currently operational systems is essential for designing suitable comparative tests of system effectiveness.

4. The set of test signals used in comparative system tests must be selected so as to be representative of the difficulties posed at each stage of the functional taxonomy, as well as the signal population of interest and the operational environment.

5. Considerations of experimental control usually dictate the use of synthetic signals injected into the actual operating system; the parameters of the injected signals must reflect the considerations outlined in No. 4 above.

6. The timing of injected signals is particularly important when the system test involves questions of operator scanning behavior, vigilance, or expectancy as to the time of appearance or nature of the target.

7. Both men and computers (or computer programmers) require comprehensive sets of signals on which to learn. The discriminations learned on the learning set must be cross-validated on an independent test set of representative signals to properly assess the effectiveness of these discriminations.

8. Individual differences among operating personnel in experience, training, innate abilities, and motivational variables must be taken into account in the design of the operational test and in the analysis of the resulting data. Such differences can otherwise result in misleading conclusions about differences between the systems in man-machine performance.

9. In the interest of equalizing or controlling for individual differences among operators, it is desirable to employ within-subject test designs in which the same personnel operate both the experimental and baseline systems during the test. If this is not possible, personnel used in the two conditions should be matched as completely as possible on all variables known to be relevant to performance.

10. Negative attitudes toward innovative systems or procedures may develop and adversely affect the operational test unless certain principles of introduction are followed. A change advocate, whose credentials are highly respected by operational personnel, can be very useful in this respect.

11. The operational test should be designed so as to minimize atypical operator motivations that stem simply from the operator's knowledge that he is participating in a test.

12. The operational test should be designed so as to avoid atypical operator "expectancy" for targets of special interest. However, this objective may have to be sacrificed somewhat in meeting the need for reliability of performance measurement.

13. Usually, operational personnel used in system tests should be representative of "average" operators. The tendency to utilize superior personnel in the experimental system should be resisted, although some test objectives might justify the use of superior operators in the baseline system.

14. When the same test personnel operate both the experimental and baseline systems, the test design should be such that unwanted performance variance is not introduced by the *order* in which the two systems are operated.

15. If the test involves round-the-clock operations, the test design and data analysis should take into account the diurnal variations in the level of arousal (alertness) of human operators.

16. In selecting criterion measures of man-machine performance by which the test outcomes will be assessed, it is essential to provide for recording of data pertinent to each aspect of the function taxonomy that is related to the test objectives. The recording schemes used may differ considerably for the man and the machine.

17. Special signal sets may have to be designed to obtain appropriate system response measures on some parts of the function taxonomy.

18. In the interest of obtaining reliable man-machine performance measures, substantial numbers of measurements should be made on similar signal inputs for each part of the function taxonomy under test.

General Conclusions

There are a large number of specific conclusions to be found interspersed throughout Volume II of this report as well as those already presented in this volume. However, we should like to emphasize here the broadest and most general conclusions that we have come to as a result of this study.

When we undertook this research, we did it in response to a felt need for a systematic design feedback loop from operating surveillance systems to the designers of future systems, and we assumed that the final results would be usable as guidelines for the design of future surveillance systems. That seemed like a reasonable objective, and we hope the results presented in various parts of these two volumes do prove to be useful to the surveillance community; we are reasonably certain that at least some of these materials will be. However, the first major conclusion we wish to present here concerns our original expectation that we would be able to develop detailed design trade-off criteria that would be applicable to the function allocation phase of the design

process. From this expectation, the reader can see some implication that we thought we might develop a "cookbook" for function allocation. We did intend to proceed as far as possible in that direction; but we also stated at the outset that our objectives were ambitious, and we were somewhat dubious of accomplishing those objectives where the human was involved in the loop, because his behavior is so task-specific. However, we thought the machine side of the equation might tend to make the problem more tractable. It now appears to us that the behavior of machines is also highly task-specific, and therefore a small set of design principles will not serve to provide ready answers to the much larger set of *specific* man-machine function allocation problems. We have already stated, and we reiterate as a major conclusion, that no "cookbook" of man-machine function allocation recipes is impending as a result of this work or any other we are aware of. Instead, the function allocation methodology that we have described must be applied to individual function allocation problems.

The second major conclusion we have come to is that many aspects of the detection, feature extraction/association, and classification functions of surveillance systems cannot be totally automated, now, or for some time to come, without a substantial sacrifice in system performance. We have concluded that man must remain in surveillance systems as a partner in the detection and post-detection processing functions for the full performance potential of new surveillance system designs to be realized. Certainly, we feel that man should be extensively machine-aided in these areas, and vice versa. But that leaves us with a considerable problem, because the function and task allocations that will successfully optimize this man-machine partnership remain to be determined. The surveillance community now needs to undertake a substantial and dedicated research and development effort, hopefully employing to advantage some of the material we present in this report,

to discover how men and machines can work most effectively together in surveillance systems.

A Word About Volume II

Volume II of this report contains a great deal of additional information that we hope will be of interest to individuals whose responsibilities include research and development on surveillance systems hardware, software, and operating personnel.

Following the introductory remarks in Chapter 1 of Volume II, we present in Chapter 2 a more detailed description of functions in specific surveillance systems and deal with some of the classified examples of those functions which are not covered in the present volume.

In Chapter 3, a more detailed description of human information processing in specific surveillance systems is provided with examples of how that processing occurs in the context of operator performance during surveillance activities.

In Chapter 4, the variable output of human information processing in surveillance systems is described in terms of objective data concerning the performance of operators in specific surveillance systems and the variables that appear to influence that performance.

In Chapter 5, more detail is presented concerning the considerations necessary for proper measurement of man-machine performance in surveillance systems with special attention devoted to problems that are unique to specific surveillance systems.

The appendices of Volume II are devoted to the detailed reporting of a number of experiments directed at the detection and classification performance of operators in specific surveillance systems.

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